Extending Collaborative Learning Modeling with Emotional Information

Olga C. Santos[1], Jesus G. Boticario[1], Raúl Cabestrero[2], Pilar Quirós[2]

[1] aDeNu Research Group. Artificial Intelligence Dept. Computer Science School. UNED
C/Juan del Rosal, 16. Madrid 28040. Spain
[2] Basic Psychology Dept. Faculty of Psychology. UNED.
C/Juan del Rosal, 10. Madrid 28040. Spain
[1]{ocsantos,jgb}@dia.uned.es, [2]{rcabestrero,pquiros}@psi.uned.es

Abstract. This work presents some initial ideas on a data mining based approach for building affective collaborative systems. In particular, we focused on the modeling issues involved in providing open affective student interaction models by using data mining techniques. The approach facilitates transferability and analysis without human intervention, and extends with emotional information previous data mining based developments.

Keywords: Collaboration, Data mining, Open models, Affective Computing.

1 Introduction

Given that affective issues play a significant role in e-learning scenarios [1, 2], in the context of the MAMIPEC project we are investigating emotions modeling in Computer Supported Collaborative Learning (CSCL), where either positive or negative emotions can emerge [3]. Positive ones are expected to bring about an increase in the number of users' interactions and accordingly the development of new collective generated knowledge. On the other hand, when individual aims collide with collective ones, negative emotions frequently arise. Under CSCL learners usually cope with more striking challenges than those present under face-to-face learning [4]. For instance, objectives of some group members can interfere with ones of others. Also, diversity in terms of levels of involvement, working styles and interaction modes frequently become overlapped within the group members. Additionally, the lack of previous common background and generally accepted point of view usually obstructs the way of getting cooperative solutions [3].

In this context, provided that Data Mining (DM) can be used for emotional information detection in CSCL [5], our goal is to extend the Collaborative Logical Framework (CLF) collaboration model [6] with emotional indicators and personality traits following a DM approach used in previous collaboration experiences [7].

2 Affective Collaborative Modeling approach

Personality traits and emotions play a key role in social and collaborative scenarios [4]. In this sense, it can be stated that personality can modulate the way the student participates on a given situation. For instance, some studies have found that participants that exhibit lower scores on extraversion and higher on mental openness prefer on-line learning tend [8]. Thus, in order to enrich adaptation in collaborative learning scenarios with affective support, the model has to take into account the user personality traits that can be influencing the user interaction behavior. It has also to consider the user affective state (i.e. pride, shame, curiosity, frustration, etc.) generated within the undergoing activity itself and the whole CSCL interaction. For this, i) context, ii) process and iii) assessment are considered key issues to model collaboration [9, 7].

The ***collaboration context*** affects students' potential and their capacity to collaborate. Information comes from data related to both students and the environment, which should be relevant to students' teamwork skills [10]. This information can be collected in the collaborative learning experience from an initial questionnaire (e.g., personal, academic and work-related data, study preferences, and personality traits).

The ***collaboration process*** involves features such as activity, initiative or acknowledgment. Relevant information can be obtained by analyzing students' interactions in communication tools such as forums [11] because of the close relationship that exists between students' collaboration and interactions. In this sense, previously we proposed a statistical analysis of the interactions in forums to discover some features that make students suitable for collaboration [6], namely student initiative, activity and regularity, as well as perceived reputation by their peers. Students' regularity indicators involve time variables because the interactions are considered over a period of time. In any case, these metrics are general in as much as they are based on non-semantic statistical indicators (e.g. number of replies, regularity of interventions, etc.) and thereby flexible enough to be potentially instantiated in diverse collaborative environments. In order to take into account affective information in these collaboration indicators, several information sources such as physiological data, keyboard and mouse interactions, explicit subjective affective information provided by learners, facial expression, etc. gathered while learners collaborate in the environment can be considered [12].

To cover aforementioned key issues, the approach we have been following offers ***collaborative assessment*** metrics based on DM process (clustering) to facilitate transferability and analysis without human intervention [7]. It also follows the open model strategy, which has shown its benefits in the educational context. This strategy uses scrutable tools that enable students to access inferred models and actively intervene in the modeling process [13], this way raising metacognitive information [7].

Our proposal for affective collaborative learning modeling is depicted in Fig. 1. In particular, to account for affective issues in the given *collaboration context* (user and environment), the approach has to be extended with an analysis of the affective reactions, elicited during the *collaboration process* within the ongoing collaboration *task* itself, and those due to the *interaction with peers* that feed the *collaboration assessment* and produce not only the *statistical indicators* proposed in [6] but also the add *affective ones*. The *affective indicators* are to be calculated with DM techniques in the light of the *collaboration assessment* by means of the *interaction content*: positive (proposing or suggesting; supporting or agreeing), negative (opposing or disagreeing) or ambivalent (information giving; inquiring; answering or specifying) as rated by both the emitter and the receiver (*interaction ratings* using weather 'overt' – subjective reports– or 'covert' –physiological or behavioral recordings– sources of information) [14]. To cope with *interactions latency*, it has to be taken into account if interaction are produced within certain time window or never take place at all –e.g. unanswered message–. On top of that, the *roles* could elicit an additional emotional reaction or modulate existing ones. Two different types have to be considered: *scripted* and *naturally emerged*. First ones are externally assigned, as a consequence of the statistical interaction indicators (i.e. information gatherer, moderator in the CLF *task* [6], etc.). Second ones emerge naturally in any collaborative work situations (i.e. task or social leadership or other types of roles that emerge in learning situations).

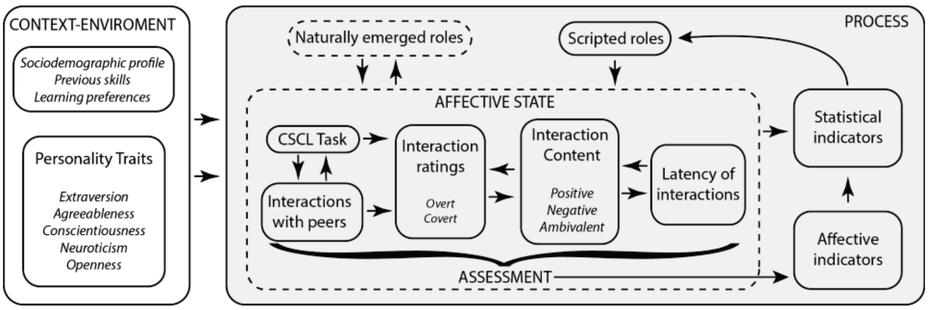

Fig. 1. Affective enriched statistical indicators in the open affective learner model

3 On-going work

To investigate how to enrich the statistical indicators with the affective ones, a CLF collaborative task was set out in Madrid's Week of Science 2012 with a total participation of 17 participants (including pilot experiments). They were asked to collaboratively solve one conundrum on a given time frame following three consecutive stages (*individual*: each participant proposes solution; *collaboration*: discussions and ratings among participants to enrich individual solutions; and *agreement*: solution proposed by moderator and discussed and rated by the rest of participants) while their collaboration interactions and affective information (i.e. personality questionnaires, physiological and behavioral recordings and subjective reports) are processed [6].

All these sources of information, along with the statistical indicators, deserve future analyses in order to refine and calibrate affective indicators and to articulate them using a DM approach. By introducing aforementioned affective issues the approach is expected to improve collaborative learning. In particular, based on our experience in developing educational recommender systems [15] those affective indicators detected will serve to develop affective educational recommendations.

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